

RNN/LSTM Data Assimilation for the Lorenz Chaotic Models

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(Tukey 1962): “ An approximate solution to the right problem is worth more than a precise solution to the wrong problem”.

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We employ Lorenz '63 ('96) model as DA pilot

<https://drive.google.com/open?id=1JaBndNTAmFyHlfvaaZYP1EOgaFceYUeH>

- Developed by Ed. Lorenz in 1963, as a simplification of work by Saltzman
- Set of 3 Ordinary Differential Equations:

$$\frac{dX}{dt} = -\sigma X + \sigma Y$$

$$\frac{dY}{dt} = -XZ + \rho X - Y$$

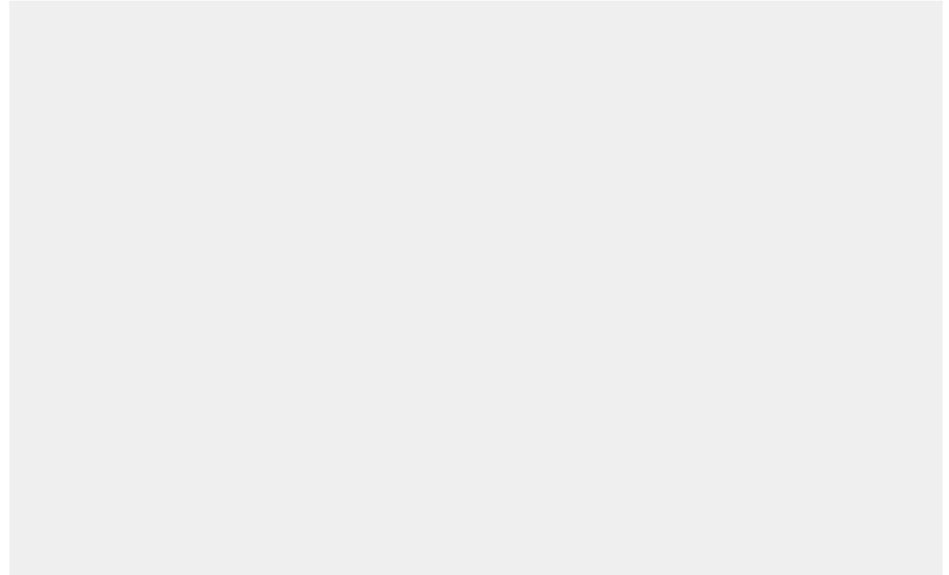
$$\frac{dZ}{dt} = XY - \beta Z$$

- Values of constants: $\sigma = 10, \beta = 8/3, \rho = 28$
- Initial values of the two Lorenz 63 plots:

Plot 1: $X = 3.01467124, Y = 2.99579101, Z = 2.98076554$

Plot 2: $X = 3.01353676, Y = 2.98556565, Z = 2.98962346$

Difference: $\Delta X = 0.00113448, \Delta Y = 0.01022536, \Delta Z = -0.00885792$

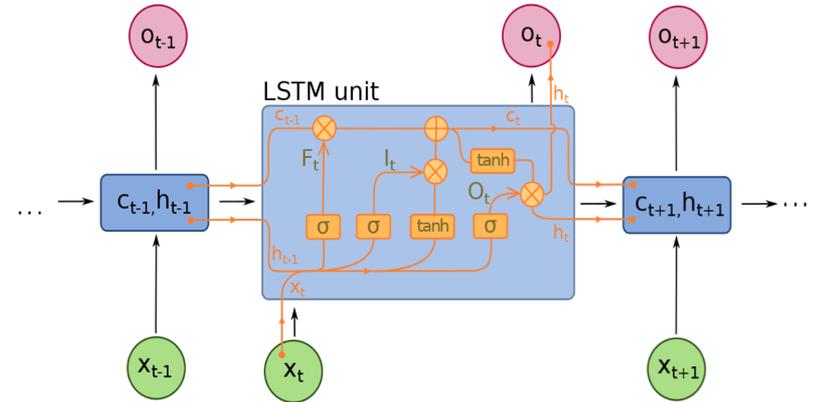


OSSE Performance Evaluation of a Machine Learning Data Assimilation Scheme

- For generating *nature's true* evolving states, we use the Lorenz '63 ('96) model with a Runge-Kutta integration scheme.
- To simulate an *imprecise model* approximation to nature, we degrade the nature run with larger time steps and random noise added to the model equations.
- The observing system is simulated by selecting arbitrary portions of data *from the true nature model* at fixed intervals of time with added noise representing observational errors.
- Ensemble predictions are made from the approximate model by *perturbing initial conditions* and adding different errors to represent different parameterizations.
- We *train the LSTM to simulate an Ensemble Kalman Filter (EnKF) data* assimilation approach using the DART framework.
- Validation of LSTM data assimilation is *compared with nature* simulation as well as EnKF simulations.

Long Short-Term Memory (LSTM) Networks

- LSTM networks are a type of Recurrent Neural Network
 - Selectively updates their internal state
 - Effectively represents temporal data
 - Avoids vanishing or exploding gradient problems
- LSTM consist of multiple gating mechanisms to control its behavior based on the internal Cell State. Intuitively, these mechanism are:
 1. Deciding what to forget
 2. Deciding what to take from input
 3. Making updates
 4. Generating outputs



Results

Training and Testing Scores for Lorenz-63 and Lorenz-96 models

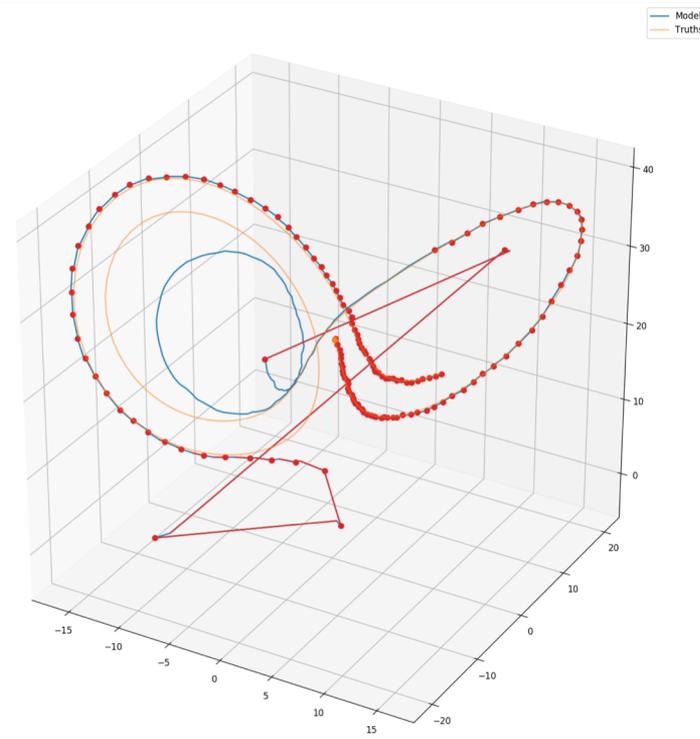
	Lorenz-63 (3 variables)	Lorenz-96 (40 Variables)
Weighted RMSE (Training)	0.37073	1.29406
Weighted RMSE (Validation)	0.37318	1.31864
Weighted RMSE (Testing)	0.26642	0.92281

Results

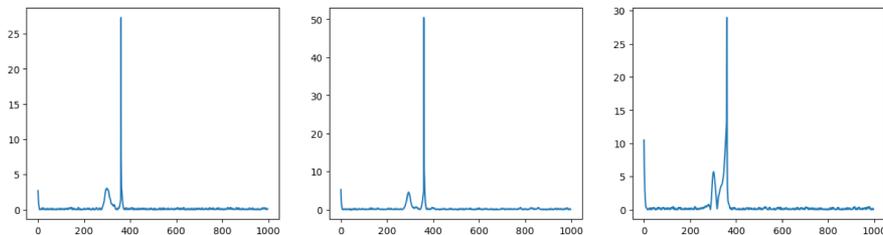
A snapshot of lorenz-63 model (with errors) forecast and data assimilation cycle using LSTM network

- Figure on the bottom is absolute difference between state and truth for each state
- Figure on the right captures the forecast and DA cycle of the model. The red dot are the start of DA cycle and the end of its tail marks the cycle's end.

Note: Observations does not exist for a section of the run.



State - Truth, Time Correspondence MAE, Run file index: 1, time_step: 3600



Conclusion

- LSTM networks can be used for Data Assimilation in Chaotic models.
 - The network can learn to estimate the process of an Ensemble Kalman Filter,
 - Largely possible due to different activation functions on intentionally designated branch for mean and variance estimation.
 - Can be used for different configurations of the same model.
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- Thank You